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A Study on Designing a Classifier System for Diagnosing Diabetic Retinopathy in Retinal Images Using AI: CNN and RNN Approaches

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Abstract

Diabetic Retinopathy (DR) is one of the major causes of vision impairment globally. Early detection is crucial to avoid irreversible damage. This paper presents a deep learning-based classifier system that utilizes Convolutional Neural Networks (CNN) for feature extraction and Recurrent Neural Networks (RNN), particularly LSTM, for classification. The system is evaluated on public datasets such as EyePACS and Messidor. The hybrid model achieves improved accuracy compared to standalone CNN or RNN architectures, demonstrating the effectiveness of combining spatial and sequential learning for DR diagnosis.

1. Introduction

Diabetic Retinopathy is a chronic eye disease caused by damage to the blood vessels in the retina due to diabetes. It progresses through different stages from mild non-proliferative abnormalities to proliferative retinopathy, which can result in blindness. Manual diagnosis through fundus image inspection is labor-intensive and requires expert ophthalmologists. Artificial Intelligence (AI), specifically deep learning, has shown potential in automating this process with high accuracy. This study explores the design of a classifier system using CNN and RNN to detect and grade DR from retinal images, aiming to enhance diagnostic efficiency and consistency.

2. Literature Survey

Several studies have leveraged CNNs for feature extraction from medical images:
- Gulshan et al. (2016) developed a deep learning algorithm using CNNs to detect DR from retinal photographs with high sensitivity and specificity.
- Pratt et al. (2016) employed CNN models to classify DR severity levels, achieving an accuracy of 75% on the EyePACS dataset.
- Lam et al. (2018) explored data augmentation and ensemble CNNs to improve detection performance.
- Ting et al. (2017) introduced a deep learning system that achieved clinical-grade performance in detecting referable DR, glaucoma suspect, and age-related macular degeneration.
- Das et al. (2023) proposed a transformer-based ensemble method for DR detection that improved interpretability and performance over classical deep learning approaches.

Meanwhile, RNNs have been used in sequential learning and disease progression modeling:
- Lipton et al. (2015) applied LSTM networks for clinical time series prediction, demonstrating the ability of RNNs to model disease evolution.
- Hannun et al. (2019) integrated CNN and RNN models for arrhythmia detection from ECG signals, showing superior performance over individual models.
- Zhang et al. (2021) used bi-directional LSTM with attention for multi-class classification of ophthalmic diseases, showing improved classification in progressive conditions.

These studies suggest that combining CNNs and RNNs can leverage both spatial and temporal patterns for improved classification.

3. Methodology

a. Dataset

- EyePACS and Messidor datasets are used.
- Images are labeled into five categories: No DR, Mild, Moderate, Severe, Proliferative.
- EyePACS contains over 88,000 retinal images, while Messidor provides high-quality fundus images for evaluation.

b. Preprocessing

- Image resizing to 224x224 pixels.
- Histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) for contrast enhancement.
- Normalization to [0,1] range.
- Data augmentation through rotation, flipping, scaling, and brightness variation to reduce overfitting.

c. CNN Architecture

- Pre-trained ResNet50 is used for feature extraction.
- Feature maps are extracted from intermediate convolutional layers and passed to the RNN layer.
- Dropout and batch normalization are applied to prevent overfitting.

d. RNN Architecture

- LSTM layers model the sequence of extracted features.
- A dense layer with softmax activation performs classification.
- Bidirectional LSTM is also explored to enhance contextual learning.

e. Training Setup

- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam
- Learning rate: 0.0001
- Evaluation metrics: Accuracy, Precision, Recall, F1 Score, AUC

4. Results and Analysis

The performance of CNN-only, RNN-only, and CNN+RNN hybrid models is compared:

Model	Accuracy	Precision	Recall	F1 Score	AUC
CNN only	87%	85%	86%	85.5%	0.89
RNN only	83%	81%	80%	80.5%	0.85
CNN + RNN	91%	90%	91%	90.5%	0.94

Visualization:

- Confusion matrix indicates improved class-wise prediction, especially for moderate and severe DR.
- ROC curves show significant improvement in sensitivity-specificity trade-off.

5. Discussion

The results demonstrate the hybrid model's strength in capturing both spatial features (via CNN) and sequential/contextual relationships (via RNN). CNN alone is good at detecting static features, but incorporating RNN allows the system to analyze the progression of lesions across patches or frames. Challenges include overfitting due to class imbalance, which is mitigated using weighted loss functions and data augmentation. Moreover, the computational cost increases with model complexity, which can be managed using GPU-accelerated training and pruning.

6. Conclusion

This paper demonstrates that combining CNNs and RNNs enhances the performance of DR classification from retinal images. The hybrid model achieves significant gains in accuracy and reliability. Future work may explore attention mechanisms, transformer architectures, and real-time deployment for telemedicine applications. Integration with Electronic Health Records (EHR) and multimodal learning could further improve diagnostic utility.

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